Predicting Financial Distress and Corporate Failure: Empirical Evidence from the Nigerian Banking Sector

Nkiri J. E.^{*}, Ofoegbu G. N.

Department of Accountancy, University of Nigeria, Nsukka, Nigeria

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Abstract This study examines the relevance of accounting based models in the prediction of financial distress and corporate failure. Using a sample of 30 commercial banks, consisting of 15 failed and 15 non failed banks during the period 2006-2020, the study utilizes the Logit and Multiple Discriminant Analysis (MDA) models using accounting information to predict the likelihood of failure within the Nigerian banking sector. The empirical results reveal that bank characteristics derived from financial statements can be used to predict corporate failure. Specifically, bank liquidity and profitability are key determinants of bank failure. The study adds to the scarce body of literature on bank failure among developing economies, by analyzing, developing and testing a prediction model in a developing economy like Nigeria. This study also offers recommendations for both policy and practice, especially for bank regulators and the management team on the need to monitor the profitability and liquidity position of banks.

Keywords Corporate Failure, Financial Distress, Bank Failure, Failure Prediction

1. Introduction

The Covid-19 pandemic has changed the global economic landscape for business organizations around the world – both small and large organizations are endangered by the pandemic. This has led to a fall in oil prices,

shutdown of industries and disruption of sporting and other social activities around the world. This development will likely threaten and possibly violate the going concern assumption of business entities, thereby magnifying the effect of the global crisis.

The threat of going bankrupt is of concern to many stakeholders of a firm including shareholders, management, employees, creditors and the government. The consequences of failure can be related to loss of investments, jobs, government revenue and a reduction in the level of economic activities in general. Corporate failure imposes severe financial and psychological damages to affected parties and, in more extreme situations, can lead to loss of lives.

As severe as failures of firms in other sectors may be, failure in the banking sector poses even greater challenges. This is because of the systemic role of the banking sector in the economy. Bank failures lead to loss of effective and efficient intermediation role of the banks and loss of public confidence in the banking system. In order to avoid the negative consequences of corporate failure, particularly the failure of banks, concerned parties are interested in improving the models used for early detection and prevention of failure as the world weathers the storm of economic downturn. There has never been a better time to minimize default risk than now. According to Hensher and Jones [20], distress forecasting helps in assessment of loan security, going concern evaluation by auditors, measurement of portfolio risk, pricing of risky bonds, credit derivatives and other securities exposed to credit risk. The fundamental question now arises as to how then can

financial distress be assessed and the risk of failure detected on a timely basis?

1.1. Statement of Problem

Developing a model that would enable stakeholders to identify possible failure in any organization has been intriguing to researchers over the years. Previous studies in this area have attempted to develop early warning models with some degree of predictive power in order to detect financial distress or failure before it actually occurs. Prior to developing quantitative measures of the performance of companies, qualitative criteria were established by rating agencies to assess the credit-worthiness of particular merchants [18]. Later on, a good number of studies in predicting the health of firms were introduced which concluded that failing firms demonstrate significantly different variable measurements from those of continuing firms [22]. For instance, Beaver [6] studied financial ratios in order to predict bankruptcy in firms, using cash flow ratios and confirmed that ratio analysis can be a useful tool in predicting financial failure [27].

Since Beaver [6] and Altman [2], significant bodies of research have applied accounting ratios in predicting corporate failure. Some of the notable models include Deakin [14], Libby [32], Blum [7], Edmister [16], Wilcox [33] and Moyer [23]. The accounting based models make use of information from the company's financial statements to assess and predict the probability of a firm going to bankruptcy within a certain period. Financial statements have played a key role in bankruptcy prediction models. Financial statements by its nature provide valuable information about the financial position, performance and cash movement patterns of an organization, as well as the value the firm has created over the period of evaluation. From elementary Accounting, the primary objective of financial statements is to guide users in making informed economic decisions – and the foremost concern in such decision making is the ability of a firm to continue operations as a going concern. This explains why financial statements have been at the center stage in most corporate failure prediction models.

However, accounting based models have been heavily criticized for lack of theoretical framework to guide the selection of variables and the backward looking nature of financial statements amongst others. For instance, Zavgren [34] argues that the variables used in accounting models have no theoretical or empirical support and the arbitrary basis of variables selection often results in a confusing array of variables used, making the models' results difficult to interpret. Charalambakis, Espenlauby and Garrett [12] also posits that accounting based models can be less informative than the market based models because they use information from financial statements which present past performance of a firm and may not convey information about its future.

Consequently, most recent studies have used market and economic variables to measure bankruptcy risk. For instance, Campbell, Hilscher and Szilagyi [9] utilized the estimated probability of financial distress obtained from a hazard model to examine distress risk priced equity markets. Further, Shumway [28], Agarwal and Taffler [29] employed discrete hazard technique to compare accounting-based versus market established models for UK firms. There seems to be a paradigm shift from the use of accounting data to market, macroeconomic and other variables in the failure prediction models on the premise of the limitations surrounding the use of accounting data.

Furthermore, the majority of extant literature focuses on modeling failure prediction in institutions other than financial institutions. Previous studies have focused more on organizations who take credit facilities with less emphasis on the credit giving institutions themselves. Financial institutions are also susceptible to distress. The consequences of financial institutions' distress are much more severe than that of non-financial organizations, hence studies on corporate failure prediction should be more focused on banks and similar institutions than what is currently the case. While there is extensive evidence on the performance of different methods, including accounting and market models in countries and regions such as the United States and Europe respectively, little evidence is known about the ability of the multiple discriminant model to predict financial distress in Nigeria. This is probably due to the lack of information required to develop appropriate models to forecast financial distress in Nigeria. The essence of this study therefore, is to fill the identified gap and assess the relevance of accounting models in the prediction of corporate failure within the contemporary business environment in Nigeria.

1.2. Research Objectives

The main objective of this study is to determine the predictive ability of accounting based models in corporate failure. The specific objectives are to:

1. Test the predictive power of Multiple Discriminant Analysis (MDA) technique in predicting corporate failure in the Nigerian banking sector.
2. Ascertain the relationship existing between a firm's profitability and the likelihood of failure.
3. Determine the relationship that exists between a firm's liquidity and the likelihood of failure.

1.3. Research Hypothesis

The following null hypotheses have been formulated for the study.

1. H_0 : The Multiple discriminant analysis model cannot be used to predict the financial distress of Nigerian banks

2. H_0 : There is no significant relationship between a firm's level of profitability and its likelihood of failure
3. H_0 : The liquidity position of a firm does not significantly affect its likelihood of failure

2. Literature Review

2.1. Definition of Bank Failure

Corporate failure in a financial services industry occurs when a fairly reasonable proportion of financial institutions in the system are unable to meet their obligations to their customers, their owners and the economy as a result of weaknesses in their financial, operational and managerial capabilities which render them either illiquid and or insolvent [11].

According to the Central Bank of Nigeria Annual Report [10], corporate failure occurs when a financial institution has a weak deposit base, is afflicted by poor management and fails to meet capitalization requirements. Hence, a financial institution is in distress when it is faced with harsh financial, operational and managerial weaknesses which make it difficult for the institution to meet its commitments to its stakeholders. Failure in the banking industry occurs when banks are either illiquid or in debt and depositors are scared of losing their deposits and so there is a breakdown of contractual obligations [15]. A bank shows early signs of failure when it is unable to meet its financial obligations as at when due [17]. This becomes obvious when a bank is hugely indebted to other banks, inability to meet depositor's demands, inability to meet operating obligations and weak capital adequacy ratio requirements among others.

Bongini, Claessens and Ferri [8] define distress to comprise of all the instances where a financial institution has received external support as well as when it was directly closed. They further expand the scope of distress to include any of the following four events:

- i). the financial institution was closed
- ii). the financial institution was merged with another financial institution;
- iii). the financial institution was recapitalized by either the Central Bank, the Deposit Insurance Corporation, or an agency specifically created to tackle the crisis
- iv). the financial institution's operations were temporarily suspended.

The definition of distress here is more comprehensive and logical as it captures the key indicators of distress. In the first instance, a financial institution will be closed where it is unable to meet its commitments and/or regulatory requirements. When the central bank or similar regulatory authority recapitalizes a financial institution, it is to prevent it from failing thereby protecting public interest. Furthermore, suspending the operations of a

financial institution is one of the actions taken by the regulatory authorities when a bank is in distress to curtail the possible damages that might occur if the bank is eventually closed. Finally, mergers within the financial sector are a common exit route for distressed firms. For example, during the bank consolidation era when Nigerian banks were asked to recapitalize N25bn before December 2005, several banks merged (as an alternative to outright failure) to meet up with the new recapitalization requirement. However, a short coming here is the fact that sometimes mergers occur due to strategic and other reasons different from financial distress.

Unuafé and Afolabi [30] defined a distressed financial institution as one with severe financial, operational and managerial weaknesses that have made it difficult for it to meet its obligations to its customers, owners and the rest of the economy as and when due. They further state that insolvency and illiquidity are two distinct but related conditions that characterize bank failure. Insolvency denotes a situation in which the totality of assets of an institution is less than the sum of its liabilities, a condition which inhibits it from performing its obligation to depositors and shareholders alike. On the other hand, illiquidity defines the problematic cash flow position of a firm.

According to Uzokwe and Ohaeri [31] a bank is deemed distressed where it cannot pay its entire depositor in full and on time. They argue that a distress situation may be either marginal or terminal. It is marginal where it is unable to pay all its depositors; the market value of its assets still overweighs the market value of its liabilities. However, in the case of terminal distress, the market value of a bank's asset decline below the market value of its liabilities. In that case, such a bank is said to have failed. The definition implies that marginal distress may not necessarily lead to failure if timely remedial actions are taken. For instance, in 2011 ten (10) Nigerian banks were adjudged by the NDIC to be in some form of distress, three of those banks successfully recapitalized while the remaining seven were absorbed by other banks.

2.2. Empirical Review

The early studies concerning ratio analysis for bankruptcy prediction were univariate studies. These studies focused on individual ratios and sometimes compared ratios of failed companies with those of successful firms. The univariate studies had important implications for future model development as they laid the groundwork for multivariate bankruptcy prediction models.

Beaver [6] is credited for being the first to propose the univariate model to attain the probability of predicting bankruptcy in firms with the use of financial ratios. Applying paired-sample design criteria (for firms in the same industry and of similar asset size), a sample of 79

failed firms and 79 non-failed firms was derived from Moody's Industrial Manual for the period from 1954 to 1964. 'Non-corporate firms, privately held firms, and non-industrial firms (e.g. public utilities, transportation companies, and financial institutions)' were not included in the sample [6]. A total of 30 ratios were selected based on their use in previous studies. The findings reveal that there were significant differences in the ratios between failed and non-failed firms over the observation period. For instance, failed firms had lower cash flow to total debt ratios and net income to total assets ratios than non-failed firms.

In order to overcome the limitations of Beaver's univariate analysis, Altman [2] pioneered the multivariate approach into the field of corporate failure. Altman [2] developed the Z score model employing the Multiple Discriminant Analysis (MDA) technique. Samples of 33 bankrupt and 33 non-bankrupt firms in the US during the period 1946–1965 were compared. The firms were in the same industry (manufacturing) and were of similar assets size. A total of 22 financial ratios were selected on the basis of frequent use in previous studies as the best indicators of predicting corporate failure. The Z score model (a five variables model) is as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.010X_5$$

Where:

X_1 = Working Capital/Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Earnings before Interest and Taxes/Total Assets

X_4 = Market Value of Equity/Book Value of Total Liabilities

X_5 = Sales/Total Assets

Z = Overall score

Since the introduction of MDA technique in failure prediction, several studies have applied the model in related studies [2,7,14,16]. However, the validity of its results was criticized because of its restrictive assumptions such as a normal distribution of ratios and equality of variance-covariance matrices of ratios for both groups. The restrictive assumptions on the application of discriminant analysis led researchers to develop other multivariate statistical tools to overcome these limitations. After the 1980s, MDA began to lose its popularity with researchers and was replaced by less demanding statistical techniques. One of the statistical techniques that requires fewer restrictive assumptions is logit analysis [5].

Ohlson [24] applied a probabilistic estimate of failure to his study and developed the so-called logit model from 105 US bankrupt firms and 2,058 US non-bankrupt firms during the period 1970–1976. Ohlson's [24] model was comprised of nine explanatory variables. The findings suggest that the logit-based model provided classification

accuracy of 96% one year prior to failure. Persons [26] used the logit model with nine (9) predictor variables drawn from 1993 – 1996 financial statements to differentiate failed from surviving financial institutions in Thailand. His study found that failed finance companies had lower profitability, lower foreign borrowing possibly due to their poorer credit rating, lower management quality, and were smaller in size.

In Nigeria, Iyoha and Udegbonam [21] used logit regression analysis to predict bank failure in Nigeria. The model was estimated using both pooled and cross-sectional data. The result indicates overall correct predictions ranging from 62% in 1991 to 88% in 1993, an indication that the model's predictive power increases over time. That is, as the date of failure draws closer, the model's predictive power equally increases. Although the results from the study were consistent with similar studies, the model suffered a major defect in that the sample used was small compared with that used in some other previous studies. The ratios used in the study were simply limited to published figures which were generally assumed to be subjective in its estimation and a number of the explanatory variables were inter-correlated.

Babajide, Olokoyo, and Adegboye [5] used the survival analysis approach to predict bank failures in Nigeria. Using a sample of 57 private banks in Nigeria (39 failed and 18 non-failed) with panel data from 2003 to 2011, the study shows that the survival of banks in Nigeria is mainly influenced by 12 predictor variables that bank regulators could watch out for to forestall bank distress. The study revealed that banks that are high on non-performing loans to total loans plus leases and high operating expenses to average total assets have a very high tendency of failure.

Omorodion and Urhoghide [25], undertook a study to predict corporate failure with particular reference to the Nigerian banking industry using CAMEL ratios. The study covered a period of five accounting years from 2011 to 2015. Multiple discriminant model, Altman's Zscore model was used to predict bank failure and the status of Nigerian banks. It was discovered that 76% of the 10 banks used for the study had their Z-score above 2.68 threshold implying that they are strong and healthy while the other 24% were within the safety region of $1.81 < Z < 2.68$. The study supports the effectiveness of using the Z-score model in corporate failure prediction.

It is evident over several decades that most researchers in this field have attempted to construct an efficient predictive model for business failure. Both new explanatory variables and new statistical techniques have been used to search for the best predictors for failure. Moreover, the majority of these studies were carried out in the US, Europe and other developed economies, with very few mirroring the underdeveloped economies like Nigeria. Furthermore, the review shows that previous studies focused more on non-financial institutions as the object of the research. Consequently, this study will attempt to fill in the recognized gaps in extant literature.

3. Methodology

3.1. Failed Firms

This study was concerned with deposit money banks operating in Nigeria. The failed set of 15 banks from which the discriminant models of the study were derived consisted of all the banks that failed from 2006 to 2020, and meeting certain criteria to ensure data completeness, consistency and reliability. Failure was defined as receivership, voluntary liquidation, takeover or absorption by another bank, winding up by court order or equivalent. Three years standardized financial statements including income statement and balance sheet were compiled and analyzed for all the companies. Table 1 contains the list of the failed banks together with their year of failure.

3.2. Non-failed Firms

In line with Taffler [29], the sample of non-failed firms was constructed differently from some conventional previous studies in that matching with the failed companies by size or financial year was not attempted, though the number of firms were made equal in line with corporate failure studies literature. Taffler argues that statistical methods only require separate multivariate normality in the constituent groups from which the discriminant function is to be constructed together with equality of their variance – covariance matrices. As a result, restricting the size of the non-failed sample to that of the bankrupt set only serves to restrict total sample size and degrees of freedom, furthermore, to make valid inferences it is necessary for the sample groups employed in the analysis to be representative of their underlying populations. Therefore, the attempted matching by company size and financial year is not accurate. Therefore, the non-failed firms should be drawn from their most recent financial statements as the

desired function is to be applied prospectively. Consequently, the financial year ended in the calendar years 2016 to 2020. The initial sample consisted of the 22 existing commercial banks in Nigeria, and 15 banks made the final sample list (as presented in Table 2), while the other seven (7) either didn't have complete data or their financial statements were yet to be released.

3.3. Variables of the Study

3.3.1. Dependent Variable of the Study

The dependent variable is failure (likelihood of failure), as defined above, is the discontinuation of business due to financial difficulties, failure to meet regulatory requirements or merger with another company where it loses its identity. Failure is a binary variable that takes the value of '1' if the firm is classified as failed and '0' if otherwise. This measure is the standard definition in corporate failure prediction studies [10,14]

3.3.2. Independent Variable of the Study

Careful analysis of extant literature provides no coherent theory underpinning the use of financial ratio analysis and only very tenuous guidance on the appropriate measures in different situations. The use of ratio appears to have grown strictly pragmatically. Consequently, the independent variables used in this study were selected on the basis of effectiveness in previous and related studies, popularity in literature, sound theoretical arguments based on the liquid asset model of the firm (Blum 1974) and suggestions by financial analysts and industry practitioners based on their experience. The independent variables of the study, also known as predictor variables, were drawn from the two important classes of financial ratios of profitability and liquidity. The ratios for the study are defined in Table 3 below.

Table 1. List of failed banks and year of failure

SN	Bank	Year of Failure
1	Liberty Bank	2006
2	Hallmark	2006
3	Eagle Bank	2006
4	Fortune Bank	2006
5	African Express Bank	2006
6	Lead Bank	2006
7	Trade Bank	2006
8	Gulf Bank	2006
9	All States Trust Bank	2006
10	Bank Phb	2011
11	Oceanic Bank	2011
12	Spring Bank	2011
13	Fin Bank	2011
14	Intercontinental Bank	2011
15	Diamond Bank	2019

Source: Field work

Table .2 List of non-failed bank

SN	Bank
1	Access Bank
2	First Bank
3	First City Monument Bank
4	Guaranty Trust Bank
5	Fidelity Bank
6	Eco Bank
7	Standard Chartered Bank
8	Citi Bank
9	Union Bank
10	Uba
11	Zenith Bank
12	Unity Bank
13	Wema Bank
14	Sterling Bank
15	Stanbic Ibtc Bank

Source: field work

Table 3. Financial statement variables

Class of Ratio	Ratio	Definition	Code
Profitability	Return on Asset	Operating profit/Total assets	Roa
	Return on Equity	Profit after tax/equity	Roe
	Retained Earnings to Total Asset	Retained earnings/total asset	Reta
	Net Profit Margin	Profit after tax/gross earnings	Patge
Liquidity	Liquid Asset to Deposit	Liquid asset/deposit	Liqdep
	Liquid Asset to Total Liabilities	Liquid asset/total liabilities	Liqtl
	Loan to Deposit Ratio	Loans/deposits	Loandep

Liquid asset is defined as cash and short term marketable securities

3.4. Data Collection

In line with this, secondary data is retrieved from the central bank of Nigeria database, Analyst data services and African financial database. Although the sample period is from 2006, data will be collected from 2001 to have at least a five-year prediction period prior to default. Therefore, the data period is from 2001 to 2020 (covering a 20 years' period). This study employs a Multiple Discriminant Analysis (MDA) with financial ratios to identify a bank in financial distress using variables available or quantifiable from annual financial reports. The study will also employ the logit model to determine which of the variables is most significant to predicting corporate failure. We believe that developing a model with publicly available data will not only answer our research questions, but will provide significant value to the regulatory authority, managers, financial analysts, and the banks themselves.

3.5. Model Development

3.5.1. The Univariate Logit Model

The objective of the univariate logistic approach is to evaluate the predictive ability of each variable for one, two and three years prior to failure [6]. The univariate logit model was also employed to determine which of the predictor variables is most significant in failure prediction. The logit model utilizes the coefficients of the independent variable(s) to predict the probability of occurrence of a dichotomous dependent variable. Specifically, the technique weights the independent variables and creates a score for each company in order to classify it as failed or healthy. The function considered in logistic regression is called the logistic function and can be written as follows:

$$P(x) = 1/(1+e^{-z}) \quad (1)$$

Where:

$P(x)$ = the probability of failure for a firm

$Z = (b_0 + b_i X_i + \alpha)$, b_0 is the intercept, while b_i the coefficient of the predictor variable and X_i is a set of predictor/independent variables, and α the error term.

3.5.2. The Multivariate Model of the MDA

Have determined which variables of performance are significant in predicting failure from the result of the univariate analysis. The significant variables are then combined together into a multivariate multiple discriminant analysis (MDA) in order to derive a discriminant index score (called the N score) which will be used in discriminating between failed and healthy banks. MDA is based on the development of a linear equation which provides an overall score used to predict whether the subject lies in either of the two (or more) groups. The MDA model is stated as follows:

Model 2

$$N = B_1 * X_1 + B_2 * X_2 + B_3 * X_3 + B_4 * X_4 \dots + B_n * X_n + a \quad (2)$$

Where

N = the Discriminant score and outcome of the MDA equation

B_i to B_n = the discriminant coefficients of the MDA equation

X_1 to X_n = the independent predictor variables.

a = a constant

4. Empirical Results

In this section we discuss descriptive statistics, univariate logistic analysis and multiple discriminant analysis.

4.1. Descriptive Statistics

A basic step for the analysis of the data is the identification of any significant differences between the two groups of firms (i.e failed and non-failed). Initially, this was accomplished through the calculation of the significant descriptive statistics for all financial ratios used in the study. Table 4 presents the mean of all the seven (7) representative variables one year prior to the year of failure.

First, the means of six variables (including ROA, ROE, PATGE, RETA, LIQ/TL and LIQ/DEP) for the non-failed firms are higher than that of the failed firms. This is expected since the six variables involved are inversely related to failure. Specifically, ROA, ROE, PAT/GE and RETA are all profitability measures and highly profitable firms are expected to have a low probability of failure compared to firms with lower levels of profitability. Furthermore, all the profitability measures (except ROE) for the failed banks had negative means while that of the

non-failed banks were positive, buttressing the point that profitability is negatively related to the probability of failure. The LIQ/TL and LIQ/DEP are measures of liquidity and for financial institutions like banks, liquidity is a critical component necessary for survival. Therefore, surviving banks are expected to have higher values of liquidity (i.e LIQ/TL and LIQ/DEP) than failed banks. On the other hand, the last ratio of LOAN/DEP has a higher mean for failed banks compared to the non-failed banks. The loan to deposit ratio shows the percentage of customer deposit that is represented in risky asset. The higher mean values for the failed banks is consistent with the researcher expectation (i.e, loan to deposit ratio is positively related with the probability of failure).

Secondly, the means of the RETA (retained earnings to total asset) and PAT/GE (profit after tax to gross earnings) for the failed group of firms present a decreasing trend as the year of failure approaches, whereas the means of the surviving firms follows an increasing trend over the same period. Thirdly, the means of the LIQTL (cash and cash equivalent to total liabilities) and LIQDEP (cash and cash equivalent to deposit) for the failed group of firms again showed a declining pattern as the year of failure approaches, while that of healthy firms did not follow any specific pattern. Finally, the means of the LOANDEP (loan to deposit) for the failed firms was increasing as the year of failure approaches, whereas that of the surviving group of firms was declining over the same time period. These patterns are all consistent with the earlier observations that profitability and liquidity are negatively related with failure and these variables deteriorate as failure approaches.

4.2. Univariate Analysis

The univariate logit model was also employed to determine which of the predictor variables is most significant in failure prediction. The logit model utilizes the coefficients of the independent variable(s) to predict the probability of occurrence of a dichotomous dependent variable. Specifically, the technique weights the independent variables and creates a score for each company in order to classify it as failed or healthy.

The liquid asset to total liabilities ratio (LIQTL) achieves nearly 90% overall correct classification for the training sample for the first year prior to failure but the classification accuracy declines to 73.3% and 63.3% in the other two years respectively. Similarly, the liquid asset to deposit ratio (LIQDEP) had high classification accuracy of 80% in years one and two before failure and 70% in the third year. The findings for the liquidity variables are not so surprising if one considers the fact that one of the shortest routes for banks to become insolvent is their inability to meet customer withdrawal demands and other obligations as they fall due.

Relatively high overall classification accuracy is also

provided by the profitability ratios for all three years prior to failure. The retained earnings to total asset ratio and profit after tax to gross earnings ratio provides 73.3% and 76.7% overall correct classification rate respectively, for the first year prior to failure. Moreover, the return on asset (ROA) and return on equity (ROE) ratios achieved 73% and 63%, respectively, overall correct classification in the first year, though both were not statistically significant.

From the univariate analysis as presented in table 5, profitability and liquidity ratios are significantly related to the probability of failure and can be used as predictors of corporate failure. In summary, univariate analysis is a useful tool for the identification of the potential predictor variables that will ultimately be part of the multivariate model.

Table 4. Descriptive Statistics

Group Statistics					
Independent Variables	Dependent variables	N	Mean	Std. Deviation	Std. Error Mean
ROA	Failed	15	-0.32735	0.88433	0.22833
	Non-failed	15	0.01849	0.01475	0.00381
ROE	Failed	15	0.01170	1.01461	0.26197
	Non-failed	15	0.13206	0.08461	0.02185
PAT/GROSSEARN (GE)	Failed	15	-1.42712	4.29119	1.10798
	Non-failed	15	0.20710	0.16164	0.04174
RE/TA	Failed	15	-0.66728	1.23313	0.31839
	Non-failed	15	-0.01603	0.20735	0.05354
CCE/TL	Failed	15	0.18505	0.34058	0.08794
	Non-failed	15	0.61419	0.14860	0.03837
CCE/DEPOSIT	Failed	15	0.26347	0.60622	0.15653
	Non-failed	15	1.01319	0.51676	0.13343
LOANS/DEPOSIT	Failed	15	0.91580	0.56893	0.14690
	Non-failed	15	0.58937	0.16631	0.04294

Table 5. Summary of Univariate logistic Regression

Year prior to failure		ROA	ROE	PATGE	RETA	LIQTL	LIQDEP	LOANDEP
1	Classification accuracy	73.30%	63.3%	76.70%	73.30%	86.70%	80%	70%
	Sig	0.16	0.186	0.097*	0.063*	0.010**	0.013**	0.061*
2	Classification accuracy	73.30%	60%	83.30%	70%	73.30%	80%	56.70%
	Sig	0.163	0.211	0.090*	0.129	0.008**	0.018**	0.189
3	Classification accuracy	60%	40%	60%	56.70%	63.30%	70%	50%
	Sig	0.253	0.324	0.197	0.235	0.149	0.058*	0.195

**Significant at the 5% level

*Significant at the 10% level

Table 6. Summary of Multivariate analysis

Years/items	1	2	3
Classification accuracy	80%	76.70%	63.30%
Sig.	0.001	0.004	0.011
Type I Error	26.70%	33.30%	33.30%
Type II Error	13.30%	13.30%	40%
Canonical Correlation (R^2)	0.802	0.666	0.587
F Stat	7.95	6.762	5.306

4.3. The Multiple Discriminant Analysis Model

Besides the univariate (simple) logistic regression presented in the previous section, the selection of the significant predictor variables was also made using the multiple discriminant analysis. The result of the univariate analysis showed that five variables consisting of RETA, PATGE, LIQTL LIQDEP and LOANDEP were significant at the 10% level of significance. However, a variable may not be statistically significant on a univariate level but when included in the multivariate model, could add to the predictive power of the model as well as increasing the overall model significance as measured by the R square. Based on this awareness, all the predictor variables were added into the multivariate analysis and different discriminant runs were carried out. After several discriminant runs, a parsimonious model consisting of three statistically significant predictor variables had the highest accuracy rate.

Table 6 presents multivariate discriminant analysis results for years one, two and three prior to failure. Results show that the statistically significant predictor variables that entered the multivariate model are: retained earnings to total asset (RETA), liquid asset to total liabilities (LIQTL), and liquid asset to deposits (LIQDEP). Interestingly, this is a parsimonious model that includes only three variables that represent the two main categories of financial ratios, i.e. profitability and liquidity. Results also show that the liquidity ratio (LIQTL) is the most significant variable which is consistent with the univariate analysis. The resulting multivariate model has a correct classification rate of 86.7% for the non-failed banks and 73.3% for the failed banks, with an overall classification rate of 80% for the first year prior to failure. The type I and type II error rates are 26.7% and 13.3% respectively. Type I error is the misclassification of a failed firm as healthy and type II error is the misclassification of a healthy firm as failed.

Multivariate results for the discriminant model two years prior to failure are also presented. The results show that the liquid asset to total liabilities ratio (LIQTL) is still the most significant variable two years prior to failure. The model correctly classifies 86.7% of the non-failed firms with a relatively lower classification rate of 60% for the failed firms, resulting in an overall classification accuracy of 73.3%. The type I and type II error rates are 40% and 13.3% respectively. Finally, the multivariate discriminant model results three years prior to failure achieved a classification accuracy rate of 60% for the non-failed firms and 66.7% for the failed group of firms with an overall classification accuracy rate of 63.3%. In summary, consistent with prior empirical evidence, the classification accuracy rate increases as the year of failure approaches, with the first year prior to failure having the highest accuracy rate.

The SPSS software produces two statistics that are roughly equivalent in interpretation to the R^2 in linear regression: the Eigenvalues and Wilks' lambda. The

former provides information on the discriminant equations produced. It uses a function called canonical correlation which is the multiple correlation between the predictors and the discriminant function. With only one function, it provides an index of overall model fit which is interpreted as being the proportion of variance explained (R^2). From table 7 the canonical correlation of 0.779 suggests the model explains 60.68% (0.779^2) of the variation in the grouping variable, i.e whether a firm is failed or non-failed. In the second and third year prior to failure, the canonical correlation was 0.666 and 0.587, suggesting that the model explains 44% and 34% of variation in the data in the respective years. Again, like the predictor variables, the explanatory power of the model reduces as the distance to the year prior to failure increases.

The Wilks' lambda indicates the significance of the discriminant function. Results from table 8 indicate that the discriminant function is highly significant ($p = 0.000$) and provides the proportion of total variability not explained, i.e it is the converse of the squared canonical correlation. So we have 39.4% unexplained variations. However, the significance of the discriminant function decreases in years two and three prior to failure.

Table 7. Table of Eigenvalues

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.539a	100.0	100.0	0.779
a. First 1 canonical discriminant functions were used in the analysis.				

Table 8. Wilk's Lambda

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	0.394	23.761	5	0.000

5. Summary and Conclusions

The primary objective of this study was the development and testing of bankruptcy prediction models for commercial banks in Nigeria. Even though several researchers attempted to develop failure prediction models, most of them used US and European data. In Nigeria, the majority of failure prediction studies were conducted in the non-financial sector and ignored the potential impact of corporate failure in the banking sector. Therefore, the need for a failure prediction model development and validation using more recent Nigerian financial data in predicting failure in the banking sector is undeniable. Data for the study consisted of 30 matched pairs of failed and non-failed Nigerian banks covering the period 2006 to 2020.

A parsimonious model including three financial variables (a profitability, and two liquidity ratios) was

developed based on a univariate logistic regression and multivariate discriminant analysis. The three variables of RETA (retained earnings to total assets), LIQTL (liquid asset to total liabilities) and LIQDEP (liquid asset to deposit) appear to be good predictors of bank failure. The results of the analysis have shown that our corporate failure model can be easily used to predict a firm's likelihood of failure and to pinpoint specific financial and operating areas that warrant attention over a three-year time horizon.

The findings of this study have important implications for bank shareholders, executives, regulatory authorities, finance analysts and other relevant stakeholders in the financial sector. First and foremost, regulatory authorities need to monitor the three ratios utilized in this model when carrying out bank examinations to determine the financial health of banks. Secondly, the model developed in this study is a veritable tool for financial analysts to use when advising clients on investment opportunities. Finally, the results from this study will add to the limited body of research in bankruptcy prediction in Nigeria.

However, a limitation of this and all prior failure prediction studies is that the models are not based on any economic theory in choosing those factors that predict failure. Even though it is evident that the extant distressed prediction studies are mainly application driven, the development of a theoretical framework for failure prediction still remains.

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